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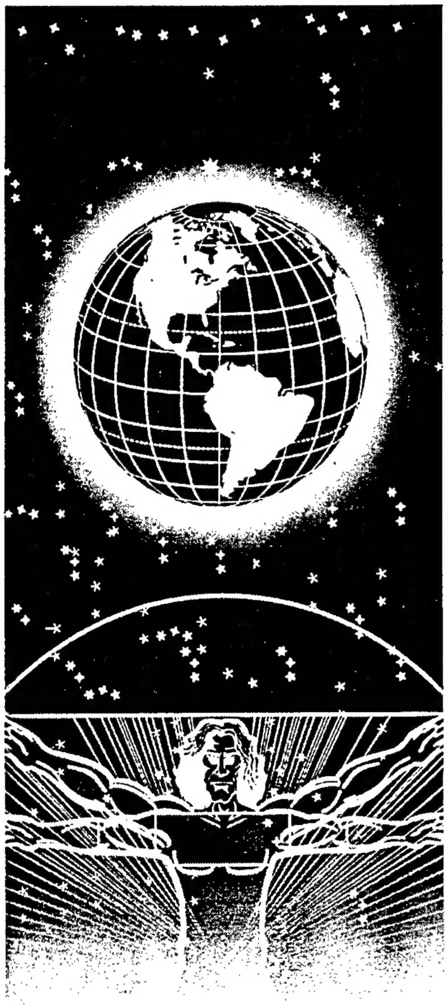

UNITED STATES AIR FORCE RESEARCH LABORATORY

REAL-TIME DECISION MAKING

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14. ABSTRACT
This paper documents three separate studies in real-time decision making under stress. The first study describes a model, Decision Making under Risk In a Vehicular Environment (DRIVE), which simulates the trade-off between two strategies for achieving a goal in real-time: 1) responding quickly to meet a deadline and 2) delaying responses to better evaluate risks. DRIVE was used to predict the performance of a time-pressured automobile driver waiting to cross an intersection, with a car approaching from a side street. Relationships were demonstrated between risk taking on the task and external measures of risk taking. The second study used DRIVE and showed that subjects attempted to cross less often before an oncoming car when it started closer to the intersection, even though the objective risk was the same regardless of starting distance. Also when the car started closer, subjects with more real-life automobile accidents were less likely to take advantage of a longer opportunity to cross first. The third study examined sleep deprivation effects in a DRIVE model. A risk-acceptance parameter in DRIVE better accounted for performance changes across fatigue conditions than a risk-perception parameter.

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Decision making, psychomotor, real-time, risk taking, time stress

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PREFACE

The research performed under this effort was conducted under Work Unit 2313-HM-11, Real-time Decision Making Under Stress. This paper documents work published in three conference proceedings. The Human Factors and Ergonomics Society proceedings included the articles titled "Assessing a Perceptual Model of Risky Real-Time Decision Making" and "Modeling the Effects of Sleep Deprivation on Real-Time Risky Decision Making." The Association for Information Systems published "Modeling Time-Pressured Risky Decision-Making."

The work was conducted by Dr Joshua B. Hurwitz of the Air Force Research Laboratory, Human Effectiveness Directorate, Warfighter Training Research Division (AFRL/HEA) at Brooks AFB TX. To complete this effort after Dr Hurwitz's departure from the division, this paper was submitted for publication by Dr Donald L. Harville, AFRL/HEAI.

Modeling Time-Pressured Risky Decision-Making

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Abstract

This paper describes a model, called Decision-Making under Risk In a Vehicular Environment (DRIVE), that simulates the trade-off between two strategies for achieving a goal in real time: 1) Responding quickly to meet a deadline and 2) delaying responses to better evaluate risks. DRIVE is used to predict the performance of an automobile driver waiting to cross an intersection as a car approaches from the cross street. In this task, the driver is punished for crashing into the oncoming car, but is also put under pressure to cross quickly. Results show a relationship between risk-taking on the intersection-crossing task and external measures of risk taking, including driving history and participation in risky activities. DRIVE model fits indicate that individual differences on this task can be accounted for by varying the decision-making parameters in the model, rather than the perceptual parameters.

Introduction

One of the hallmarks of time-pressured risky tasks is that decision-makers often face a tradeoff between quickly achieving a goal to gain some reward or delaying a response to avoid a potential loss. In these situations, a rapid response may be desirable if a delay reduces potential payoffs, whereas a delayed response may allow more time to process risk information. For example, if there is pressure to quickly reach a destination, an automobile driver crossing an intersection might decide to cross in front of an oncoming car rather than wait for that car to cross first. On the other hand, the driver might wait to better estimate of its arrival time at the intersection.

On tasks such as these, the processes underlying performance could be divided into two categories: risk perception and acceptance. Risk perception refers to mechanisms such as time estimation that underlie evaluation of the hazards inherent in an activity, whereas risk acceptance refers to the decision to execute a response in light of that evaluation. Researchers generally favor the idea that individual differences in risk acceptance underlie real-time risk taking (e,g, Wilde, Claxton-Oldfield, & Platenius, 1985). However, in many situations, a logical argument could be made for either component. In the example above, the driver could 1) overestimate the oncoming car's time to arrival and therefore cross first, or 2) accurately estimate arrival time, but accept the risk and decide to cross first anyway.

<u>The DRIVE Model</u>. In order to evaluate whether risk perception or acceptance contribute to risk taking, a model was developed that incorporates both perceptual and decisional mechanisms for making risky decisions on the crossing task. This model, Decision Making under Risk in a Vehicular Environment, or DRIVE, uses non-linear perceptual functions to estimate the oncoming car's speed and distance, as well as the time it will take for the crossing driver to reach the path of the oncoming car (Hurwitz, 1996). Free parameters in these functions determine how sensitive the model is to the true speeds, distances and times.

Using these estimates, DRIVE continuously evaluates the oncoming car's projected distance from the intersection. The projected distance, D_t, is the model's prediction of how far the oncoming car will be from the intersection when 1) a crossing response is initiated at time *t* and 2) the crossing car reaches the path of the oncoming car. Once D_t is calculated, DRIVE's decision-making mechanism determines how much it affects crossing probabilities.

In the decision-making mechanism, the probability of initiating the crossing response at time *t*, $P(R_t)$, is an exponential function of D_t, so that

$$P(R_t) = 1 - e^{-c|D_t|}$$

This function is similar to the exponential generalization gradient that Shepard (1987) has used to account for performance on perceptual discrimination tasks. The free parameter, c ($c \geq 0$), determines the degree to which the model's evaluation of risk, as represented by D_t, affects its probability of crossing. For example, if $c = 0$, then DRIVE predicts that the driver will never cross the intersection, so the value of the projected distance is irrelevant. For larger values of c, the model gets increasingly "risky", avoiding crossing only given smaller projected distances. For $c \rightarrow \infty$, DRIVE predicts that a driver will avoid crossing only when $D_t = 0$.

<u>Objective</u>. The critical question was whether differences among risk groups could be accounted for by DRIVE's perceptual or decision-making mechanisms. To address this question, high- and low-risk drivers were identified based on external measures of risk taking, such as driving history and participation in risky activities. DRIVE was then fitted to these drivers' response data from a simulated intersection-crossing task. The results were analyzed to determine how much the fit improved when some of the model's free parameters were varied across groups whereas others remained fixed.

Using this method, the risk-perception hypothesis would be supported if DRIVE's perceptual-processing mechanisms significantly account for differences across groups. However, the risk-acceptance hypothesis would be supported if the c parameter, which is associated with

DRIVE's decision-making function, best accounts for these differences. For example, consider the case in which the values of the risk-perception parameters in DRIVE (i.e. those that regulate sensitivity to speed, time and distance) vary across groups. If allowing these parameter values to vary in this way significantly improves the fit of the model, compared to keeping them fixed across groups, then this would provide evidence that group differences in risk taking are due to differences in risk perception. On the other hand, if varying the value of the *c* parameter (i.e. the free parameter for the decision mechanism) across groups significantly improves the fit compared to keeping its value fixed, then this would provide evidence that individual differences in risk acceptance best account for group differences. In other words, if the best-fitting version of DRIVE assumes that there are group differences in the decision-making parameter but no differences in perceptual parameters, then this would provide evidence that both high- and low-risk individuals process risk information similarly, but have different levels of risk acceptance.

Method

Subjects. Subjects were 122 drivers, 79 males and 43 females, living in the Chicago metropolitan area. All were paid a minimum of $30 for participating in this study, plus up to $10 more depending upon their performance. They ranged in age from 16 to 67 years, with a mean of 32.8 and a median of 29.5 (s.d. = 11.8). Most (91) had been convicted of at least one moving traffic violation in 1996.

Procedure. Subjects were instructed that they were playing the role of a driver waiting to cross an intersection as a car approached from the cross street, and that they could cross at any time by pressing a button on the joystick. They were then given 256 trials, each of which presented a 3D scene of the oncoming car shown from the crossing driver's point of view. The trials varied in 1) the oncoming car's starting distance (250′ or 500′ from the intersection), 2) the time available to cross in front of that car (0, 400, 900 and 2100 ms.), and 3) the time it took for the crossing car to cross the intersection (4 or 8 secs.).

Time pressure was implemented in this task by displaying a digital timer at the bottom of the screen. On each trial, the timer started at some value between about 3125 and 11500, and decreased at a rate such that it reached 0 by the end of the trial. The starting value depended on the conditions, and incorporated a random component to prevent the timer from acting as a cue on when to respond. When a successful crossing occurred, the subject received the number of points on the timer when the crossing was initiated, and when a crash occurred, the subject lost four times the initial value on the timer. Subjects earning more points were given more money at the end of the study.

Covariate tests. Besides the crossing task, subjects were also presented with tasks and questionnaires that measured risk perception and acceptance. One measure of risk perception was a velocity estimation task. This task was just like the crossing task, except subjects used the joystick to continuously judge the speed of the oncoming car. Accuracy was estimated using the slope of the regression line relating the estimated and true velocities.

Measures of risk acceptance included two questionnaires on risky activities, a sensation-seeking questionnaire (Heino, van der Molen & Wilde, 1996), a driving history questionnaire and a driver opinion survey (Wark, 1992). One risky-activities questionnaire asked how often subjects participated in high- and low-risk activities, including dangerous outdoors activities, racing activities and risky financial activities. The second asked subjects to rate the riskiness of these activities. The sensation-seeking questionnaire asked about preferences for engaging in highly stimulating activities. The driver history questionnaire asked subjects about their history of accidents and violations, as well as how long they had been driving and how much driving they do. The Driver Opinion Survey asked subjects their beliefs about various driving activities, such as racing other vehicles and speeding, and about traffic law enforcement, driver training, and drinking and driving.

Results

Risk groups were derived from factor scores obtained from a Principle Components Analysis of the covariate tests. This PCA was constrained to have a two-factor solution. In the results, lower age, preference for racing in the driver opinion survey, sensation-seeking tendency, velocity-estimation ability, and tendency to engage in risky outdoor activities loaded most strongly on the first factor, which was called the risk-taking factor. Higher numbers of accidents, violations, and miles-per-week driven in the previous 5 years loaded most strongly on the second factor, which was called the driver risk-taking factor. Given these results and the small number of females, four groups of males were defined based on a median split of the risk-taking and driver risk-taking factor scores, and two groups of females were defined based on a median split of the driver risk-taking factor.

The data for the model fits was each group's cumulative crossing probability at 100-ms increments in each condition. For example, consider the condition in which the oncoming car approaches from 500 feet away, the subject is given a fast car (i.e. one that crosses the intersection in 4 sec) and there is no opportunity to cross in front of the oncoming car. The trials in this condition were divided into 100-ms time steps, and, for each group, a cumulative crossing probability of having crossed was computed for every time step. This same probability function was computed for the other 15 conditions as well.

DRIVE was fitted to this data using a hill-climbing search to obtain the best parameter estimates. The fit criterion

was the weighted sum of squared deviations between observed and predicted values. There were 7 free parameters in the model: 3 for sensitivity to velocity, 2 for sensitivity to time, 1 for sensitivity to distance, and 1 (the *c* parameter) for decision-making. The first search, called s_0, assumed that all groups had the same values for all of the parameters. Then, 7 searches were done, each of which had 1 parameter varying across the groups, while the others remained fixed at the estimates derived from search s_0. A final search, s_7, was also performed in which all 7 parameters varied across groups.

Model Fits. Several criteria were used to establish which variants of DRIVE fit best. The best-fitting model was considered the one that produced the lowest sum of squares and the highest correlation between observed and predicted values. The fit of such a model also would not significantly differ from the fit of s_7, the version of DRIVE in which all parameters varied across all groups. Finally, the fit of the best-fitting model would significantly differ from the fit of s_0, the version in which all parameter values were the same across all groups.

Results (see Table 1) show that the best-fitting version of DRIVE was the one in which the *c* parameter for the decision-making mechanism varied across groups. Estimates for this parameter showed that, in general, the projected distance at which high-risk drivers stopped responding was smaller than the one at which low-risk drivers stopped responding. The fact that all estimates were held constant across groups except the one for the decision-making parameter (*c*) suggests that all subjects had equal abilities to compute the projected distances. However, when faced with smaller projected distances, high-risk subjects attempted a crossing anyway.

Discussion

While this test and the DRIVE model have obvious applications to driving, they also have more general relevance to many time-stressed decision-making tasks. These include tasks in which 1) risks fluctuate over time, 2) there is some reward for responding rapidly, but 3) the decision-maker must determine at each moment whether sufficient information has accumulated to make a risky response at that time. For example, strategic decision-makers in the Air Force often need to decide when to allocate aircraft to engagements despite having limited information about enemy strengths and positions. Opportunities may arise to attack enemy positions, but any delays to gather more information could allow the enemy sufficient time to eliminate these opportunities. On the other hand, not having sufficient intelligence about an adversary could be hazardous since it might place friendly aircrews at risk. The success or failure of these types of decisions could have a major impact on the execution of a larger engagement. Thus, understanding how these decisions are made could help in modeling how faulty decision-makers influence major conflicts.

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Table 1. Comparison of model fits assuming that a parameter for one mechanism varies across groups, and the parameters for the other mechanisms remain fixed.

Mechanism varying across groups	Sum of Squares	Correlation	Comparisons: With s_0 Chi Square	df	p	With s_7 Chi Square	df	p
Decision	12.08	0.90	31.43	5	0.000	15.63	30	0.986
Distance	16.08	0.86	5.33	5	0.377	41.73	30	0.075
Time	14.41	0.90	31.07	5	0.000	15.99	30	0.950
Speed	14.76	0.87	16.22	5	0.283	30.84	30	0.514

ASSESSING A PERCEPTUAL MODEL OF RISKY REAL-TIME DECISION MAKING

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A new model of real-time risky decision making is introduced that predicts tradeoffs between processing and risk taking during driving. This model, called Decision-Making under Risk in a Vehicle, or DRIVE, was fitted to data from a task in which subjects decided when to cross an intersection as a car approached from the cross street. Results showed that subjects attempted to cross less often before the oncoming car when it started closer to the intersection, even though objective risk was the same regardless of starting distance. Also, when the car started closer, subjects who reported having more real-life automobile accidents were less likely to take advantage of a longer opportunity to cross first. These results, along with results from fitting DRIVE to the data, suggest that risk-taking effects can be accounted for by a model of risk perception, and not by a model of risk acceptance.

Two questions in research on risky real-time decision making are how a decision maker (1) integrates real-time information and (2) judges risk levels to decide on the nature and timing of risky real-time responses. For example, drivers are often faced with making maneuvers that have a small probability of producing an accident. However, there can be incentives to take such risks because of time pressures. The goal of the research presented here is to identify and model processes underlying such risk taking.

Up until now, major theories have treated this issue as a problem of risk acceptance, but have lacked detailed mechanisms for assessing effects and individual differences that are due to risk perception. For example, models such as Risk Homeostasis Theory (RHT; Aschenbrenner & Biehl, 1993; Jannssen, 1988; Streff & Geller, 1988; Wilde, 1976; Wilde, Claxton-Oldfield & Platenius, 1985) do not explain how, under specific conditions, information is processed and integrated to time risky responses. Lacking well-specified processing mechanisms, these theories cannot separate errors due to poor distance- and velocity-estimation abilities from those due to risk taking.

Consider the case in which a driver decides when to cross an intersection. She may take some time to process information about oncoming cars, but if she takes too long, she might not arrive on time at her destination. If she crosses before sufficiently processing information about these cars, she might risk colliding with one of them. She may risk crossing quickly because they are far away, but there is a potential for error because of the tendency to underestimate distances for objects that are in motion relative to an observer (Harte, 1975) and are far from the observer (Foley, 1980). Given such errors, the driver may underestimate a car's speed and mistakenly assume that she can cross safely and quickly.

The Model. The study presented here introduces a model of real-time decision making that incorporates these distortions, and accounts for how drivers trade off processing time and risk taking. This model, Decision-Making under Risk in a Vehicle, or DRIVE, simulates how drivers make choices in real time when faced with incentives to take risks.

According to DRIVE, a driver decides when to cross by comparing an oncoming car's perceived and projected distances. The more similar these two distances are, the more cautious the driver will be. The perceived distance is the oncoming car's actual distance, coupled with error (Foley, 1980). The projected distance is the driver's estimate of how far the oncoming car would go in the driver's travel time, which is the time it takes the driver's car to reach and cross over the path of the oncoming car. Formally, the projected distance is the driver's travel time multiplied by the driver's estimate of the oncoming car's velocity.

The estimate of a car's velocity, v_t, at time t is derived from moment-to-moment changes, ΔD_t, in the car's perceived distance and from the driver's preexisting bias, k, about how fast that car should

be traveling. Formally,

$$v_t = v_{t-1} + [(\Delta D_t - v_{t-1})f_t + (k - v_{t-1})g_t]h_t (1)$$

where f_t, g_t, and h_t are sampling rates. The changes in perceived distance can be interpreted as affecting risk perception because they rely on information from the environment. The bias, on the other hand, can be interpreted as influencing risk acceptance, because it is independent of perceptual input.

While the bias is constant over time, changes in perceived distance increase as the car approaches because of distortions in computing distance in 3-dimensional space (Foley, 1980). The distorted distance, D_t, at time t is d_t^{γ} (Stevens & Galanter, 1957), where d_t is the true distance and $0 < \gamma \leq 1$. Given these distortions, a distant car traveling at a given velocity appears to be traveling more slowly than a closer car traveling at the same velocity, and an oncoming car traveling at a fixed velocity appears to be accelerating.

Effects of Bias on DRIVE. In estimating the velocity of an oncoming car, a driver adjusts the mixture of bias and perceptual input over time. It is more difficult to process the movements of a distant car, so the driver relies more on bias and less on perceptual input. However, as the car gets closer, the driver relies more on perceptual input and less on bias.

The bias can influence DRIVE's prediction of risk taking. If the model is biased to underestimate the velocity, then it predicts that the driver will more likely respond prior to obtaining sufficient information from perceptual input. However, if the bias overestimates the velocity, then DRIVE predicts that the driver will be more cautious, and will wait until the car is closer before deciding when to cross. In this case, DRIVE simulates the vacillation process that is often part of time-limited decision making (Busemeyer & Townsend, 1993; Janis & Mann, 1977; Swenson, 1992).

One final component of DRIVE is its assumption that, at each moment in time, drivers learn more about faster cars, so that $h_t = v_{t-1} + \beta$. This assumption about velocity-based learning makes sense given that a faster oncoming car poses more of a danger to a driver should he decide to cross first.

METHOD

Subjects

Subjects were 145 Air Force recruits, 89 males and 56 females, ranging in age from 17 to 35 years, with a mean age of 20.8 years. All except 3 subjects knew how to drive. The average age at which subjects reported having started driving was 15.3 years, with a range of 8 to 25 years. The average age at which they reported receiving their driver's license was 16.5 years, with a range of 14 to 25 years.

Procedure

On each trial, subjects were presented with a 3-dimensional scene depicting a "car" on a road approaching an intersection from the side (Figure 1). The "virtual eye", the direction of view on the computer screen, displayed this scene from the point of view of a driver waiting to cross the intersection from the cross street. The subject could cross at any time during this scene by pressing the mouse button. Each trial ended with feedback indicating whether the subject had crossed safely, collided or not responded.

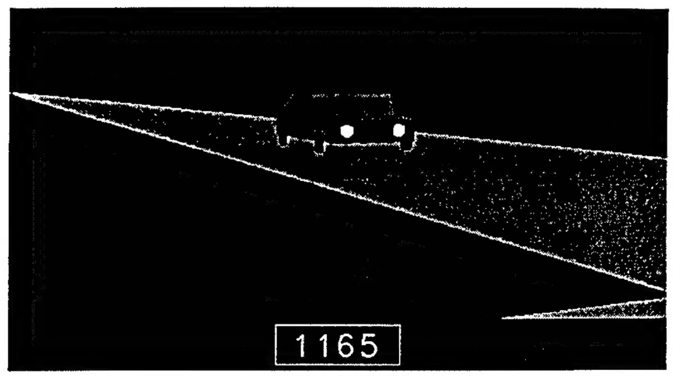

Figure 1. A scene from the crossing task in which a car is approaching the intersection. The number at the bottom shows the points earned if a successful crossing is initiated at this time during the trial.

On trials in which subjects received points, a timer was presented below the 3-dimensional scene. The numbers on the timer started at some value p_0 and ended either at 0 if the subject had not responded quickly enough, or at some value p_t. At the end of the trial, subjects were told how many points they gained or lost, and how many they had accumulated thus far. They gained points for fast, successful crossings and lost points for collisions. Their cumulative points never fell below 0.

Trial Sequences. The sequences of trials were set up so that subjects had an initial 64 trials to practice without points, followed by 64 trials with points feedback. The practice and points trials were divided into 4 16-trial blocks. On half the blocks, the subject's car took 4 secs. to cross, and on the remaining blocks, it

took 8 secs.. Subjects were told which car they would have at the beginning of each block.

On half the trials in each block, the oncoming car started 250 feet away from the intersection, and on the other half, it started 500 feet away. The trials were further subdivided according to the window of opportunity available for crossing prior to the oncoming car: 0, 400, 900 and 2100 msecs. During a block of 16 trials, each window was presented on 2 trials in each distance condition, and all window X distance conditions were presented in a random order.

RESULTS AND DISCUSSION

The results and model fits presented below will show that a model of risk perception, such as DRIVE, provides detailed and accurate predictions of data that cannot be accounted for by risk-acceptance models such as Risk Homeostasis Theory. The reason why RHT cannot account for these data is that differences in risk taking were observed across conditions that were equally dangerous.

One outcome was that subjects attempted to cross first more often when the oncoming car started from farther away ($F(1,144) = 280$, MSE = 0.10, $p < .0001$, $R^2 = 0.66$). Another result showed that subjects were sensitive to the window of opportunity, making more attempts to cross first as the window got longer ($F(3,432) = 90$, MSE = 0.06, $p < .0001$, $R^2 = 0.38$). However, this sensitivity was greater when the oncoming car started closer to the intersection ($F(3,432) = 16$, MSE = 0.04, $p < .0001$, $R^2 = 0.10$).

Attempts to cross first produced collisions more often with a relatively small window of opportunity ($F(3,432) = 439$, MSE = 0.09, $p < .0001$, $R^2 = 0.75$). Collisions were also more likely when the oncoming car started from farther away ($F(1,144) = 140$, MSE = 0.04, $p < .0001$, $R^2 = 0.49$).

These results suggest that risk-taking arose mainly from differences in risk perception. The fact that the oncoming car started from farther away could not have produced risk compensation because objective risk levels, as represented by the windows of opportunity, were equal across those conditions. So there was no change in objective risk to compensate for.

Individual differences and model fits. Further analyses were performed using an index of accident rates derived from a self-reported driving history. Only 48 subjects were used for this analysis, because of suspected lack of reliability in the self reports. Results showed that drivers who reported having more accidents in their real-life driving were less likely to attempt to cross first when the oncoming car started from 250 feet away and when there was a 2100-msec. window of opportunity ($r = 0.42$, $t(46) = 3.14$, $p < 0.003$). An attempt to cross first is defined as a response that leads either to a successful first crossing or to an accident. Given that almost all attempts were successful in the 2100-msec. condition, it appears that subjects with fewer accidents were more sensitive to the opportunity to cross first under this condition.

Using the same accident-rate index derived from the self-report measure, subjects were divided into high-accident (N=12) and low-accident (N=36) groups for the purposes of the model fits. For each group, DRIVE was fitted to cumulative response probability curves for all 16 cells in the design (2 car speeds X 2 distances X 4 windows of opportunity). Each cumulative probability was an average for a given condition over all subjects in a group, and was computed for every 33-msec. time slice as the oncoming car approached the intersection.

In the 250-foot condition, DRIVE predicted the tendency for low-accident subjects to attempt more first crossings than high-accident subjects when a window of opportunity was available (Figure 2). Also, analyses of DRIVE's parameter estimates revealed that the fit to the high-accident group data produced a greater tendency to use the bias, when compared to the fit to low-accident group data. Finally, in the high-accident fit, DRIVE was less able to discriminate when it was safe versus when it was unsafe to cross. These results suggest that group differences may have been due to differences in the ability to process the information necessary to accurately assess the risk.

Model comparisons. Aside from showing DRIVE's prediction of group differences, Figure 2 also shows that DRIVE was better than three other models at predicting attempts to cross first. The results show that eliminating some of the perceptual mechanisms in DRIVE reduced its ability to predict key attributes of the results.

In particular, DRIVE_2D, a model that did not distort perceived distances ($\gamma = 1$), underestimated the probability of attempting to cross first. Furthermore, this model did not predict the increase in attempts with longer windows of opportunity. This occurred mainly because not distorting perceived distances brought them closer to the projected distances, making the model more cautious than DRIVE.

Unlike DRIVE_2D, DRIVE_PS overestimated the probability of attempting to cross first. This second version of DRIVE excluded bias from velocity estimates, so that $g_t = 0$ in Equation 1. The bias in DRIVE was set fairly high, so eliminating it made the model more risky.

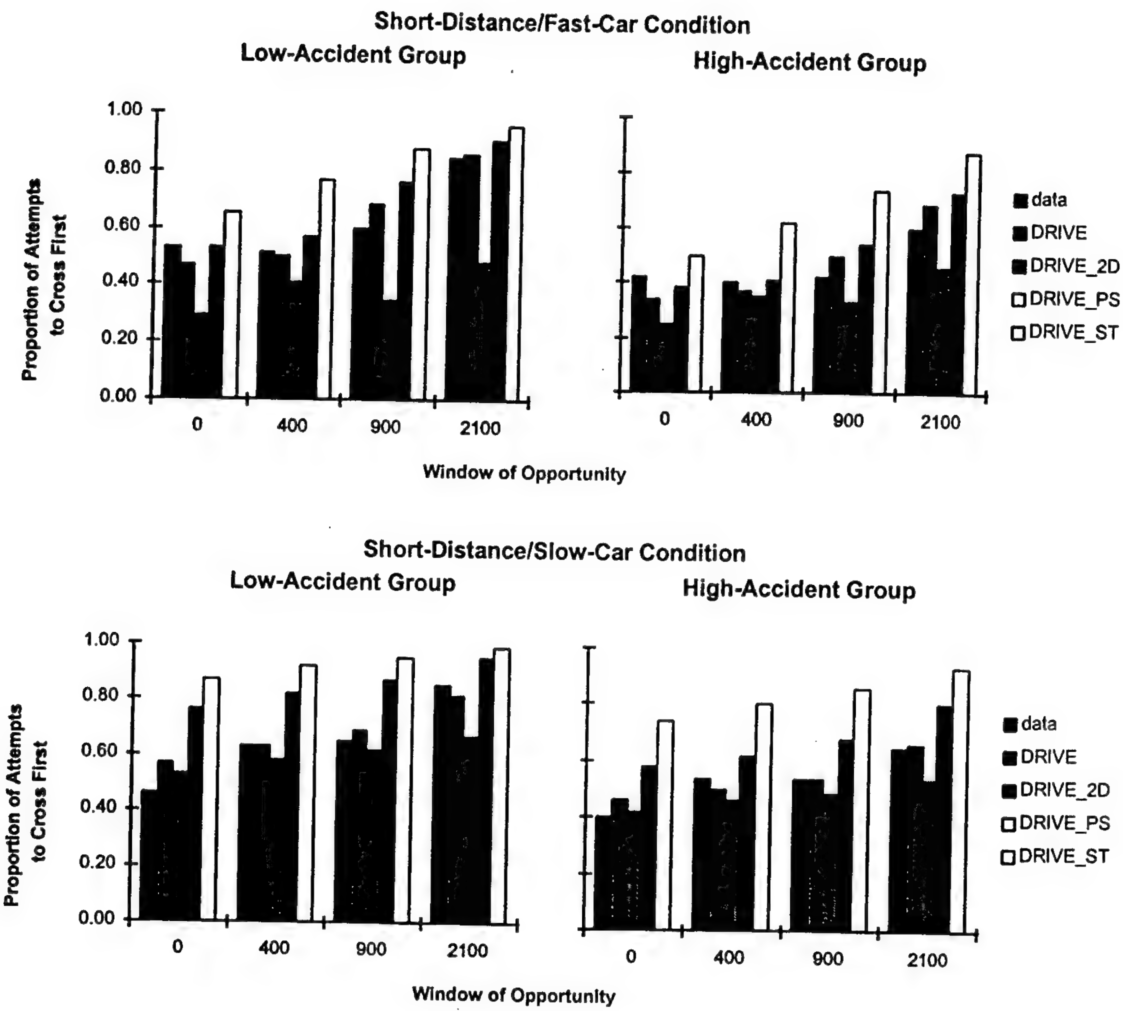

Figure 2. Data and model predictions for the short-distance (250-foot) condition.

Finally, DRIVE_ST, a model without velocity-based learning ($h_t = \beta$), also overestimated attempts to cross first. DRIVE's velocity estimate increased as the oncoming car approached the intersection, causing DRIVE to learn faster. The estimates for DRIVE_ST, however, remained low, making it riskier than DRIVE.

Future efforts. These model-fitting results were obtained by using DRIVE's parameter estimates, and then constraining some of the parameters to produce the restricted model. For example, to produce DRIVE_PS, the parameter that regulates DRIVE's sampling rate for the bias, g_t, was set to 0. A stronger test would be to fit each restricted model to the data, and then assess how well it predicts an independent set of data. For example, in a follow-up study, we are asking subjects for continuous velocity estimates of oncoming cars, as well as for intersection-crossing responses. Each model can be compared for its accuracy in predicting velocity estimates using parameters estimated from the crossing task data, with only a slight change in that model's response generation mechanism.

One better test of the model's accuracy at predicting individual differences would be to fit it to individual subject data, rather than to mean data as was presented here. Parameter estimates could then be correlated with criterion variables to assess the model's predictive validity. Also, the estimates could be factor analyzed along with other laboratory variables to assess how they relate to general cognitive and psychomotor abilities.

Finally, we hope to improve our criterion measures by obtaining objective driving history data to supplement the self-report data used in this study. We will also select subjects on the basis of their history of moving violations. Hopefully, selecting from a population that is more diverse than our restricted sample of young Air Force recruits will allow for a more rigorous test of DRIVE's validity.

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MODELING THE EFFECTS OF SLEEP DEPRIVATION ON REAL-TIME RISKY DECISION-MAKING

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Increased real-time risk-taking under sleep loss could be marked by changes in risk perception or acceptance. Risk-perception processes are those involved in estimating real-time parameters such as the speeds and distances of hazardous objects. Risk-acceptance processes relate to response choices given risk estimates. Risk-taking under fatigue was studied using a simulated intersection-crossing driving task in which subjects decided when it was safe to cross an intersection as an oncoming car approached from the cross street. The subjects performed this task at 3-hour intervals over a 36-hour period without sleep. Results were modeled using a model of real-time risky decision making that has perceptual components that process speed, time and distance information, and a decisional component for accepting risk. Results showed that varying a parameter for the decisional component across sessions best accounted for variations in performance relating to time of day.

INTRODUCTION

One of the questions in research on risky real-time decision-making is how much risk taking is controlled by risk perception and how much is controlled by risk acceptance. In real-time situations, such as automobile driving or tactical decision-making, risk perception relates to processes underlying judgments of distance, time and speed. These judgments produce predictions of the relative positions of two cars or of friendly and enemy forces at some time in the future. Such predictions amount to estimates of the hazards involved in executing a driving maneuver or in ordering friendly forces to pursue some objective.

While real-time risk perception produces estimates of risk levels, risk acceptance involves processes that generate risky responses in light of those estimates. A driver might decide to cross an intersection even though a car is rapidly approaching from the cross street. A commander might decide to overtake an enemy position even though superior enemy forces are in the general vicinity. In both cases, the responses are risky if they are based on incomplete risk information or faulty perception.

Sleep deprivation

The influence of risk perception and acceptance on risk taking is especially relevant in addressing how sleep deprivation affects real-time risky decision-making. This issue is important because fatigue increases the frequency of mishaps. For example, driving accidents peak in the middle of the night (Pline, 1992), when the circadian rhythm is typically at its lowest.

Evidence suggests that components that could affect risk perception deteriorate with sleep deprivation. For example, some studies show that d' in signal detection decreases with increasing sleep deprivation (Angus & Condon, 1985; Horne, Anderson & Wilkinson, 1983), while other work (Colquhoun, P., 1982) shows deterioration in working memory capacity. However, the most common finding is that attentional lapses increase at times when the circadian rhythm is typically at its lowest (e.g., Babkoff, Genser, Sing, Thorne & Hegge, 1985).

In 3-dimensional real-time performance, these types of perceptual limitations could impact on estimating risk in real time. Accurate risk perception requires sustained attention to continuously estimate changes in the distance of potential hazards. Attentional lapses may prevent the decision-maker from sampling frequently enough from the movements of potentially hazardous objects to estimate their speeds and their potential to cause a collision or other loss.

Sleep loss and risk acceptance

While these results suggest that risk perception deteriorates with sleep deprivation, it is also reasonable to assume that risk-acceptance processes are affected as well. A sleep-deprived decision-maker may accept more risk to counteract the effects of sleep loss and remain engaged in a task. This is a reasonable assumption given results showing that performance under fatigue deteriorates greatest on tasks considered boring or uninteresting (Gaillard & Steyvers, 1989), and that incentives to perform well counteract fatigue effects (Horne, J.A. & Pettitt, A.N., 1985).

Alternatively, sleep loss could make decision-makers rely less on controlled processes and more on automated

processes, even if the automated responses are riskier. Such responses could be riskier because the decision-maker does not attend to information about environmental hazards, and instead gives some stereotyped or well-practiced response. Previous studies of visual perception have shown a shift toward automated responding under fatigue conditions (e.g., Soetens, Hueting & Wauters, 1992). Shingledecker and Holding (1974) found that fatigued subjects on a route-finding task chose easier routes over more difficult ones, even though there was a greater risk of failure associated with the easier routes. Angus and Condon (1985) found on an inspection task that during the post-lunch "dip" and at 11PM there was an increasing tendency for subjects to favor speed over accuracy.

Measuring risk perception and acceptance

One problem in measuring risk acceptance is that, for many situations, a logical argument could be made that either risk perception or acceptance is responsible for risk taking under those conditions. In the intersection-crossing example, a driver could overestimate how long it will take for an oncoming car to arrive at the intersection, or could accurately estimate arrival time, accept the risk, and decide to cross first anyway. Such a driver might accept the risk assuming that the oncoming driver is going to slow down to avoid a collision.

One approach to separately measuring risk acceptance and perception is to develop a model that incorporates both components, and to fit the model to risk data collected from sleep-deprived subjects. The model's parameter estimates can then be used as indicators of whether changes in risk perception or acceptance best account for the changes in risk taking brought on by sleep loss. Using this approach, one can infer the mechanisms underlying risk taking during sleep loss, and whether they correspond to the circadian rhythm.

DRIVE

The model used here to predict risk-taking under sleep loss is called Decision-Making under Risk in a Vehicular Environment, or DRIVE (Hurwitz, 1996, in press; Figure 1). This model has thus far been used to predict performance on a task in which a driver (driving "car *x*" in figure 1) is waiting to cross an intersection as an oncoming car ("car *y*" in figure 1) approaches from the cross street. The driver decides when to cross by pressing the joystick trigger, and can 1) cross successfully in front of the oncoming car, 2) cross after the oncoming car has crossed, or 3) collide with the oncoming car.

DRIVE has functions for both evaluating and accepting risk on this task. It uses non-linear perceptual functions to estimate the oncoming car's speed and distance, and to estimate the time it will take for the crossing driver to reach the path of the oncoming car. Free parameters in all of these functions determine how sensitive the model is to the true speeds, distances and times.

Using its estimates of speed, distance and time, DRIVE continuously evaluates the oncoming car's projected distance from the intersection. The projected distance is the model's prediction of how far that car will be from the intersection when the crossing car reaches its path. The probability of a crossing response is an exponential function (Shepard, 1987) of this distance, with a free parameter that determines how small the distance must be in order for the probability to approach 0. Essentially, this parameter affects DRIVE's risk acceptance by determining the degree to which its evaluation of risk, as represented by the projected distance estimate, affects its probability of crossing.

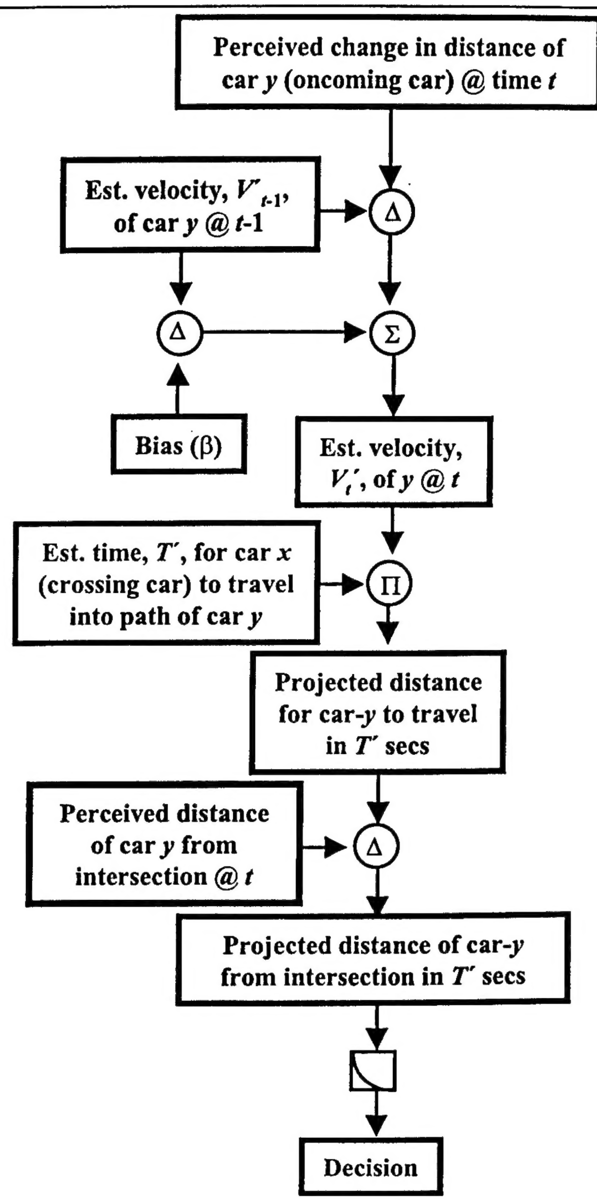

Figure 1. Component processes of the DRIVE model.

Objective

The critical question was whether changes in risk-taking on a simulated intersection-crossing task could be accounted for best by DRIVE's perceptual or decision-making mechanisms. To address this question, subjects repeatedly performed the task at 3-hour intervals over a 36-hour period of sleep deprivation. DRIVE was then fitted to these drivers' response data. The results were then analyzed to determine how much the fit improved when free parameters associated with the perceptual-processing mechanisms or the exponential risk-acceptance function were allowed to vary across test sessions.

METHOD

Subjects

There were 24 subjects, 12 males and 12 females, with a mean age of 24.3 years, a standard deviation of 4.44 years, and a range from 18 to 34 years. Each subject received $590 at the end of the study for having completed the entire study.

Procedure

Subjects attended a number of testing sessions during the course of a week, and were given the same battery of tests during each session. They started with one practice session per day on Monday, Tuesday, Wednesday and Thursday, and then went through 13 fatigue sessions at 3-hour intervals starting Friday at 8:00 PM and going through Sunday at 9:00 AM. They were instructed to wake up anywhere from 6:00 AM to 8:00 AM on Friday, so, if this instruction was followed, they would have had 48 hours of sleep deprivation by the time the last fatigue session was completed on Sunday. Finally, the subjects participated in a follow-up session at 6:00 PM the following Tuesday, after having had two days to rest up from the fatigue sessions.

Task

For the crossing task, the subjects were instructed that they were playing the role of a driver waiting to cross an intersection, and that they could cross at any time by pressing a button on the joystick. On each trial, they were presented with a PC-based simulation of 3-dimensional scene depicting a "car" on a road approaching the intersection. This scene was presented from the point of view of the crossing driver. The oncoming car approached the intersection from either 250 or 500 feet away, and there was 0, 400, 900 or 2100 ms available for the subject to make a successful crossing in front of that car. When the joystick button was pressed, the subject's car either 1) safely crossed the intersection in 4 or 8 seconds, or 2) crashed into the oncoming car. Given the 2 starting distances for the oncoming car, the 4 opportunities to cross in front of that car, and the 2 crossing times (i.e. speeds) for the subject's car, there were a total of 16 conditions.

Time pressure was implemented in this task by displaying a digital timer at the bottom of the screen. On each trial, the timer started at some value between about 3125 and 11500, and decreased at a rate such that it reached 0 by the end of the trial. The starting value depended on the conditions, and incorporated a random component to prevent the timer from acting as a cue on when to respond. When a successful crossing occurred, the subject received the number of points that were present on the timer when the crossing was initiated. When a crash occurred, the subject lost four times value that was shown on the timer when the trial began.

RESULTS

Response function and search algorithm

The data for the fits of DRIVE were the cumulative crossing probabilities at 100-ms increments for all the conditions. For example, consider the condition in which the oncoming car approaches from 500 feet away, the subject is given a fast car (i.e. one that crosses the intersection in 4 sec) and there is no opportunity to cross in front of the oncoming car. The trials in this condition were divided into 100-ms time steps, and, for each testing session, a cumulative crossing probability of having crossed was computed for every time step. For each testing session, this same response function was computed for the other 15 conditions as well.

Typically, this response function rose at the beginning of a trial, reached a plateau, and then rose again at the end of the trial. The initial rise was due to subjects taking the opportunity to cross in front of the oncoming car. In some conditions, this rise was almost non-existent because the oncoming car was traveling fast enough that subjects mostly detected no opportunity to cross first. The plateau occurred because the oncoming car had reached a point at which subjects predicted that a crossing would lead to a collision. The final rise in the response function was due to subjects crossing after the oncoming car had reached the intersection. This was also occasionally missing when the oncoming car was traveling slowly enough for subjects to attempt to cross first almost all the time.

Model fits

DRIVE was fitted to this data using a hill-climbing search to obtain the best parameter estimates. The fit criterion was the weighted sum of squared deviations between observed and predicted values. The weights used were inversely related to the number of 100-ms time steps in a condition, so that all conditions influenced the fit equally regardless of how long they lasted. The first search, called s_0, assumed that all sessions had the same parameter values. Then, one of the parameters was allowed to vary across the sessions, while the others remained fixed at the estimates derived from s_0. A final search, s_7, was also performed in which all 7 parameters varied across session.

In comparing the various fits, the best-fitting model would be the one that produces the lowest sum of squared

deviations and the highest correlation between observed and predicted values. The fit of such a model also would not be significantly different from the fit of s_7, the version of DRIVE in which all parameters varied across all test sessions. Finally, the fit of the best-fitting model would be significantly different from the fit of s_0, the version in which all parameter values were assumed to be the same across all sessions.

			Mechanism with parameter(s) varying across sessions			
			Decision	Dist. Estim.	Time Estim.	Speed Estim.
Sum of Squares			46.29	48.50	48.86	48.35
Correlation			0.73	0.72	0.72	0.72
Comparisons	with s_0	χ^2	42.83	34.66	27.74	30.56
		df	4	4	4	4
		p	0.000	0.000	0.000	0.001
	with s_7	$\chi 2$	48.17	56.34	63.26	60.44
		df	24	24	24	24
		p	0.002	0.000	0.000	0.001

Table 1. Fit statistics for versions of the DRIVE model.

Fit Results

As Table 1 shows, by these criteria, the best-fitting version of DRIVE was the one in which the parameter for the exponential decision-making mechanism varied across sessions. This fit produced the smallest sum-of-squares between observed and predicted values, the highest chi-square when compared to the fit with no parameters varying across conditions (s_0), and the lowest chi-square when compared to the fit with all of the parameters varying (s_7). A similar result was found when the model was fit to various risk groups (Hurwitz, 1997), with variation in the decision parameter best accounting for group differences.

Estimates for the decision-making parameter show that the value of the parameter rises during the practice sessions, and continues to rise during the fatigue session (Figure 2). It then abruptly falls at 1 AM on the second evening of the fatigue sessions, and stays relatively low even through the follow-up session.

The size of the parameter represents the degree to which the model stretches the scale for the projected distance before generating the response probability. The larger the value of the parameter, the more the projected-distance scale is stretched, and the more likely the model is to predict greater risk taking with small projected distances. In Figure 2, for example, the model predicted greater risk taking with small projected distances at 1300 hours (1 PM) on Saturday during the fatigue sessions than it did during practice session 1.

These model fits indicate that subjects may have accepted more risk under fatigue. However, this was not uniformly true across all of the sleep-loss sessions. The fits also suggest that risk taking actually decreased when the circadian rhythm would typically be at its lowest, during early morning and mid-afternoon hours. The one exception was on the second evening, when the decrease in risk acceptance extended throughout the evening. This implies that moderate fatigue may increase risk acceptance when the circadian rhythm is higher, but that extreme fatigue may actually lower risk taking.

DISCUSSION

The main result was that performance changes across fatigue conditions were better accounted for by changing DRIVE's risk-acceptance parameter than by changing its risk-perception parameters. In previous work (Hurwitz, in press), differences across driver risk groups were also better accounted for by the risk-acceptance parameter. In this study, the groups were defined based on a history of traffic accidents and violations. The results indicated that the parameter estimate for the exponential risk-acceptance mechanism was higher for groups with a history of higher accident and violation rates. Thus, the outcomes of both studies suggest that risk acceptance, rather than risk perception, may be the critical component underlying risk taking on the intersection-crossing task.

The fact that the risk-perception parameters are not as effective in accounting for driver-group differences or changes with sleep deprivation may stem from the nature of the task itself. This task may not sufficiently strain attentional capabilities to detect individual differences in selective attention that typically correlate with crash rates (Avolio, Kroeck, & Panek, 1985; Mihal & Barrett, 1976). Furthermore, the task may not be sensitive enough to detect attentional lapses that are common with fatigue (Babkoff et al., 1985). While the task presented here was designed to measure risk acceptance, perhaps a more demanding task with more traffic and more response choices would produce individual-differences for both risk perception and acceptance.

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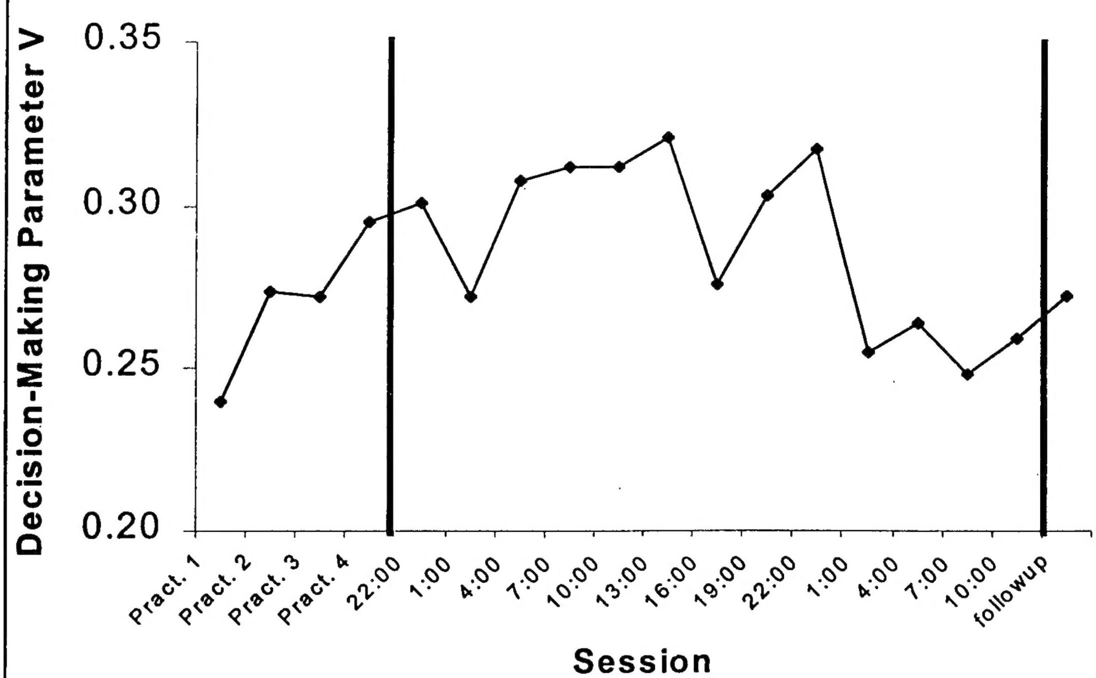

Figure 2. Change in decision-making parameter value across practice, fatigue and follow-up test sessions. Fatigue sessions indicate the time at which the crossing task was given.